The IOA Systems for CHiME-6 Challenge

Hangting Chen[1,2], *Pengyuan Zhang*[*1,2], *Qian Shi*[1,2], *Zuozhen Liu*[1,2]

[1]Key Laboratory of Speech Acoustics & Content Understanding, Institute of Acoustics, CAS, China
[2]University of Chinese Academy of Sciences, Beijing, China

{chenhangting, zhangpengyuan, shiqian, liuzuozhen}@hccl.ioa.ac.cn

Abstract

The paper presents IOA's submission to the 6th CHiME Challenge. Our systems include the front-end enhancement combining deep learning-based and probabilistic model-based source separation, training data augmentation, acoustic modeling with multi-channel branches and system fusion. Tested on the evaluation sets, our best system for Track 1 Category A/B has yielded $35.11\%/34.53\%$ word error rate (WER) respectively, with an absolute reduction of $16.18\%/16.76\%$ compared with the baseline model.

1. System overview

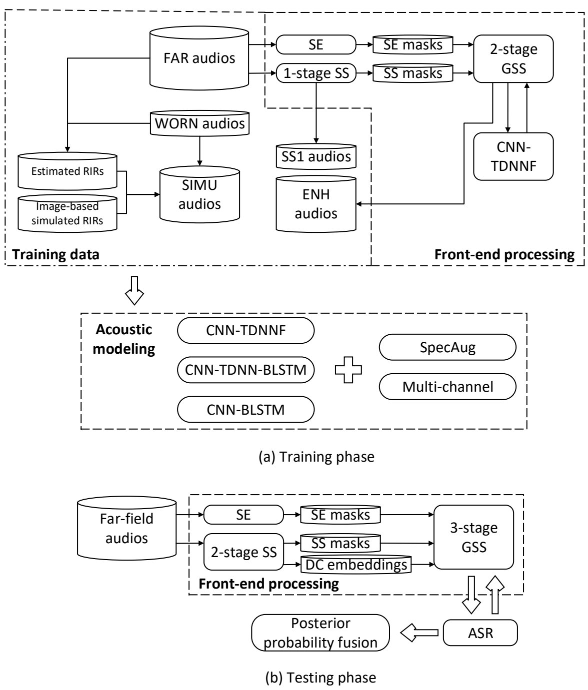

Figure 1: *The (a) training and (b) testing phase of our systems.*

This report describes our contribution to the 6th CHiME challenge (CHiME-6), which provides speech data recorded in the real party scenario via microphone arrays and presents extreme speech overlap and unrestrained speaking styles [1]. Our systems are designed for Track 1 Category A/B. Figure 1 shows the framework of the training and testing procedures of our systems. It consists 5 parts, including deep learning-based single-channel speech separation (SS), multi-channel speech enhancement with guided source separation (GSS), training data augmentation, acoustic modeling and system combination.

In the training phase, we first train 1-stage SS models for each speaker in each session (SS1), a universal speech enhancement model (SE). The separated audios serve as a part of training database. Then a 2-stage GSS is initialized with the speaker and noise masks, further refined by ASR alignments. 3 types of acoustic models with multi-channel branches are trained with the dataset augmented with additional data.

In the testing phase, we train 2-stage speech separation models (SS2). A 3-stage GSS is deployed to perform multi-channel speech separation. The final results are obtained with posterior probability fusion.

The detailed descriptions of the systems and the word error rate (WER) results on the development (Dev.) and evaluation (Eval.) sets can be found in the following sections.

2. Front-end processing

2.1. Deep learning-based single channel source separation

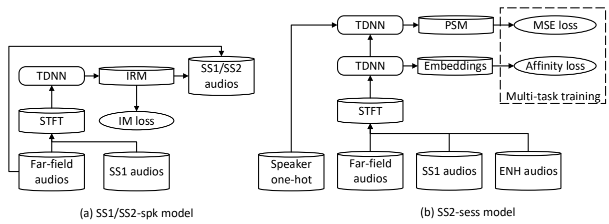

Figure 2: *The (a) SS1/2-spk and (b) SS2-sess model for single channel speaker separation.*

The deep learning-based single-channel source separation is to generate source masks and embeddings. The SS1-spk and SS2-spk models are trained for each speaker in each session. The SE models are training with progressive learning, similar with [2]. The SS2-sess models serve as unified models to separate speakers as well as to extract source embeddings for each session. The model is trained to optimize the multi-task loss of affinity matrix [3] and phase-sensitive masks [4] (Figure 2). In our experiments, the SS1-spk models utilize non-overlapping utterances. The SS2-spk and SS2-sess models additionally use audios separated by SS1-spk and enhanced by 1-stage GSS.

2.2. Multi-channel guided source separation

We have developed the multi-channel separation based on the GSS [5]. The overall framework of systems is given in Figure 3. All the 24 channels audios are dereverbed with the weighted prediction error (WPE) [6]. SS and SE masks combined with annotations and alignments are served as an initialization of the

* Pengyuan Zhang is the corresponding author.

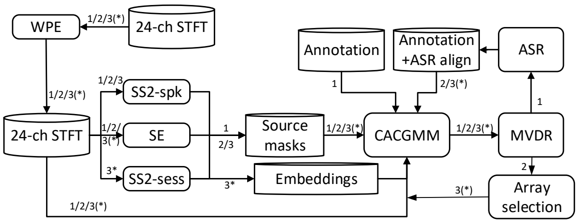

Figure 3: *The frame work of* 3*-stage GSS. The number represents the data flow in the* 1,2,3(*) *stages individually.*

complex angular central Gaussian model (CACGMM). After iterations, the masks representing the target speaker and the inference are used to do beamforming.

In the 3-stage GSS, the 2nd stage utilizes alignment generated by the 1st stage, the 3rd stage selects the microphones based on the signal-to-noise (SNR) information from the 2nd stage. The 3^*-stage differs by using von Mises-Fisher (vMF)-CACGMM model [7] with embeddings from SS2-sess and selecting microphones with the fusion of SNR- and coherency-based [8] methods.

The 2-stage GSS, which is adopted in the training phase to generate enough data, consists of the 1st and 3nd stages. The array selection is in random to output 7-fold data, named ENH in Figure 1.

Each stage's performance of the front-end processing is presented in Table 1.

Table 1: *The Front-end results on the Dev. with CNN-TDNNF trained with WORN and ENH data [9].*

Stage	Baseline	1	2	3	3^*
WER(%)	45.42	43.02	42.62	42.14	**41.75**

3. Acoustic models

3.1. Training data and settings

The whole training set contains worn headset data (WORN), far-field microphone array data (FAR), simulated data (SIMU), multi-channel enhanced data (ENH), totally 4 parts. The FAR data is made up of the original far-filed audios and single-channel audios enhanced by SS1 models. The SIMU data is generated by convolving the WORN data with image-based simulated room impulse responses (RIRs) and estimated RIRs calculated by the far and worn audio pairs. Moreover, it is observed that the short utterance combination can benefit the performance of the acoustic models. We have created 2 training sets, a small one with only WORN and ENH data, a large one with all mentioned data.

3.2. Networks

Totally 9 acoustic models are trained for the final fusion. They are derived from CNN-TDNNF trained on the small set, CNN-TDNN-BLSTM trained on the large set and CNN-BLSTM trained on the large set (Table 2). A multi-channel branch is introduced with CNN architectures, whose input is log power spectral (LPS) and magnitude squared coherence (MSC) [10].

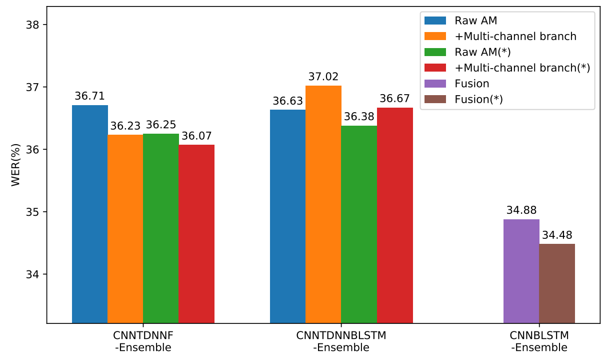

Figure 4: *The ensemble results of different architectures on the Dev.. * means the audio is from* 3^**-stage GSS.*

The branch is trained in 2 ways, partial update and full update [12].

The results of the acoustic model ensemble are plotted in Figure 4. The fusion adopts the weighted average of log posterior probability according to Table 2.

Table 2: *An overview of the number of single- and multi-channel acoustic models.*

Architecture	**Single-channel**	**Multi-channel**
CNN-TDNNF	3	3
CNN-TDNN-BLSTM	3	2
CNN-BLSTM	3	1

4. Conclusion

We present the performance details of our fusion systems, which are tuned on the Dev. set and tested on the Eval. set. For Category B, a language model based on the recurrent neural network (RNN) is trained for rescore. It yields around 0.6% improvement for both Dev. and Eval. sets.

Table 3: *The WERs (%) of our best systems for Category A and B.*

Category	**Session**	**Dining**	**Kitchen**	**Living**	**Ave**
A	S02	38.30	38.50	31.59	33.55
	S09	32.25	30.07	29.23	
	S01	29.58	48.49	42.72	35.11
	S21	29.76	39.66	28.60	
B	S02	37.51	38.02	31.06	32.92
	S09	31.54	29.69	28.11	
	S01	28.83	48.61	41.64	34.53
	S21	29.14	39.39	28.03	

5. References

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